Using Climate Mode Indices to Forecast Carbon Monoxide Variability in Fire-Prone Southern Hemisphere Regions

William S. Daniels[1], D. M. Hammerling[1], R. R. Buchholz[2], H. M. Worden[2], F. Ahamad[3]

[1]Colorado School of Mines, [2]National Center for Atmospheric Research, [3]AQ Expert Solutions

Motivation

- Certain regions in the Southern Hemisphere experience extreme carbon monoxide (CO) anomalies as a result of biomass burning.
- Two goals for this work:
  1. Build interpretable models that enable scientific insight into fire drivers.
  2. Predict CO anomalies as a proxy for fire intensity at useful lead times.

Observational Data Sets

- We model deseasonalized, week-averaged CO anomalies from MOPITT within the Maritime Southeast Asia (MSEA) region.

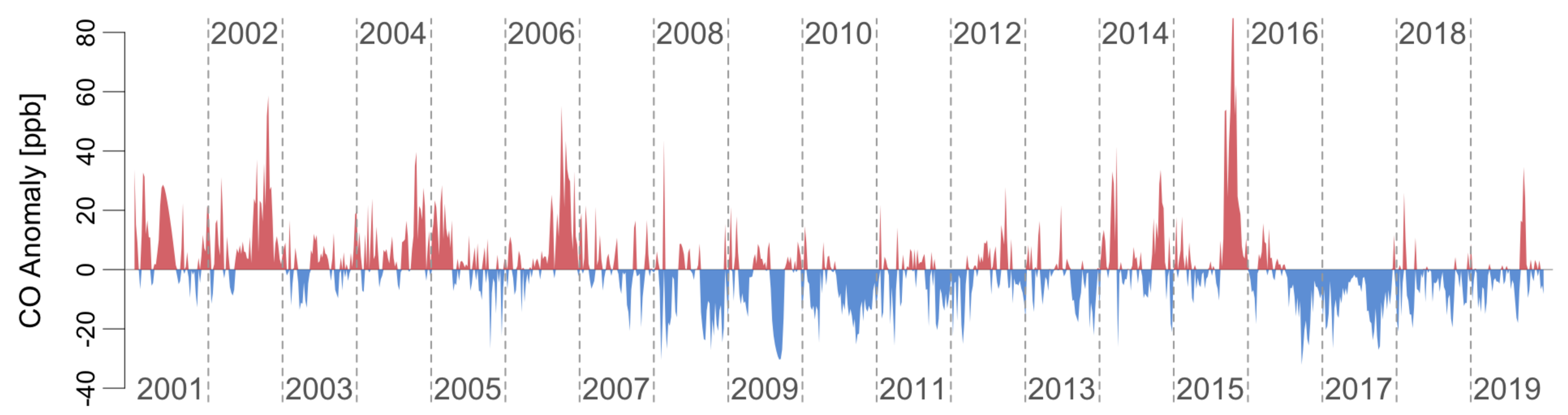

Figure 1: Week averaged, deseasonalized CO anomalies in MSEA region.

- We use five climate mode indices as predictor variables: Niño 3.4, DMI, TSA, SAM, and OLR as a proxy for the MJO.
- Climate indices are related to regional climate (e.g., rainfall), which affects drought conditions, vegetation growth, and ultimately fire intensity and CO concentrations.

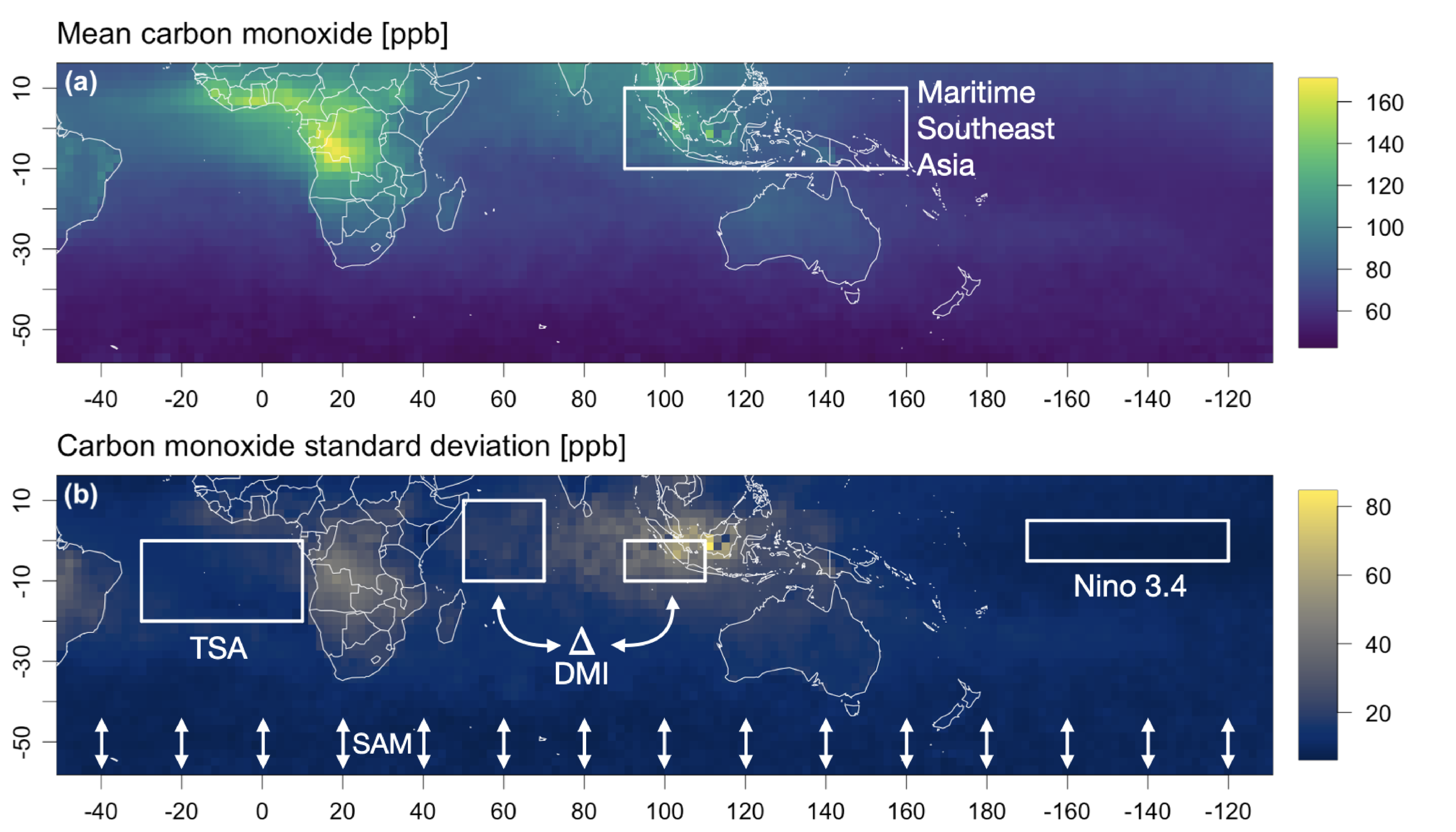

Figure 2: (a) Average of all MOPITT CO observations during 2015 with MSEA region overlaid in white. (b) CO standard deviation during the same time period with the spatial range of influence of four climate mode indices overlaid in white.

Statistical Model

- We use multiple linear regression with interaction terms to estimate the relationship between CO and climate indices.

$$CO(t) = \mu + \sum_i a_i\, \chi_i(t-\tau_i) + \sum_j b_j\, \chi_j(t-\tau_j)^2 + \sum_{k,l} c_{k,l}\, \chi_k(t-\tau_k)\, \chi_l(t-\tau_l) + \epsilon(t)$$

- $CO(t)$ is the CO anomaly in a given region at time t.
- $\chi_{i,j,k,l}$ are the climate indices with coefficients a_i, b_j, and $c_{k,l}$.
- $\tau_{i,j,k,l}$ are the lag values for each index in weeks.
- μ is a constant mean displacement, and $\epsilon(t)$ is an error term.

- Variable and lag selection is done via a flexible regularization framework with free parameter γ controlling the size of the model.

Goal #1: Interpretable Models

- By varying γ, we get a selection of optimally performing models that decrease in size. Terms are listed in the format "`name_lag`."

Smaller γ

```
               Est (Std. Error)
(Intercept)      0.3 (0.70)
nino_4           7.6 (0.83)
dmi_1            5.7 (0.79)
dmi_12          -6.1 (0.75)
dmi_43           1.8 (0.65)
tsa_3           -2.2 (0.64)
sam_2           -3.6 (0.61)
sam_38          -2.2 (0.64)
sam_51          -1.6 (0.63)
olr_1            2.3 (0.74)
olr_13           3.4 (0.71)
nino_4:olr_1     3.2 (0.66)
nino_4:dmi_1     3.2 (0.81)
dmi_1:dmi_12    -4.5 (0.56)
nino_4:sam_51   -4.2 (0.77)
tsa_3:olr_1     -2.3 (0.63)
sam_2:olr_13    -2.1 (0.68)
nino_4:sam_2    -1.8 (0.70)

Standard error: 10.22
Multiple R-squared:  0.70
Adjusted R-squared:  0.68
DF: 17
```

Larger γ

```
               Est (Std. Error)
(Intercept)     -1.6 (0.78)
nino_4           7.2 (0.78)
dmi_4            7.2 (0.93)
dmi_12          -8.0 (0.87)
sam_51          -3.1 (0.67)
olr_1            3.5 (0.79)
I(nino_4^2)      2.5 (0.54)
nino_4:olr_1     3.5 (0.76)
nino_4:dmi_12 -6.5 (0.77)
sam_51:olr_1  -2.3 (0.67)

Standard error: 11.42
Multiple R-squared:  0.61
Adjusted R-squared:  0.60
DF: 9
```

Figure 3: Optimal model for MSEA region at two different sizes.

- `nino_4` with a positive coefficient indicates that dry conditions from a positive Nino 3.4 anomaly take four weeks to increase fire intensity and subsequent CO concentrations in MSEA.
- `dmi_12` with a negative coefficient suggests that vegetation growth preceding fire season increases fire intensity, while `dmi_1` with a positive coefficient suggests that subsequent dry conditions further increase fire intensity in MSEA.

Goal #2: Predictions at Useful Lead Times

- Including the OLR (as a proxy for MJO) increases predictive skill, especially during the largest anomalies (e.g., 2006 and 2015).

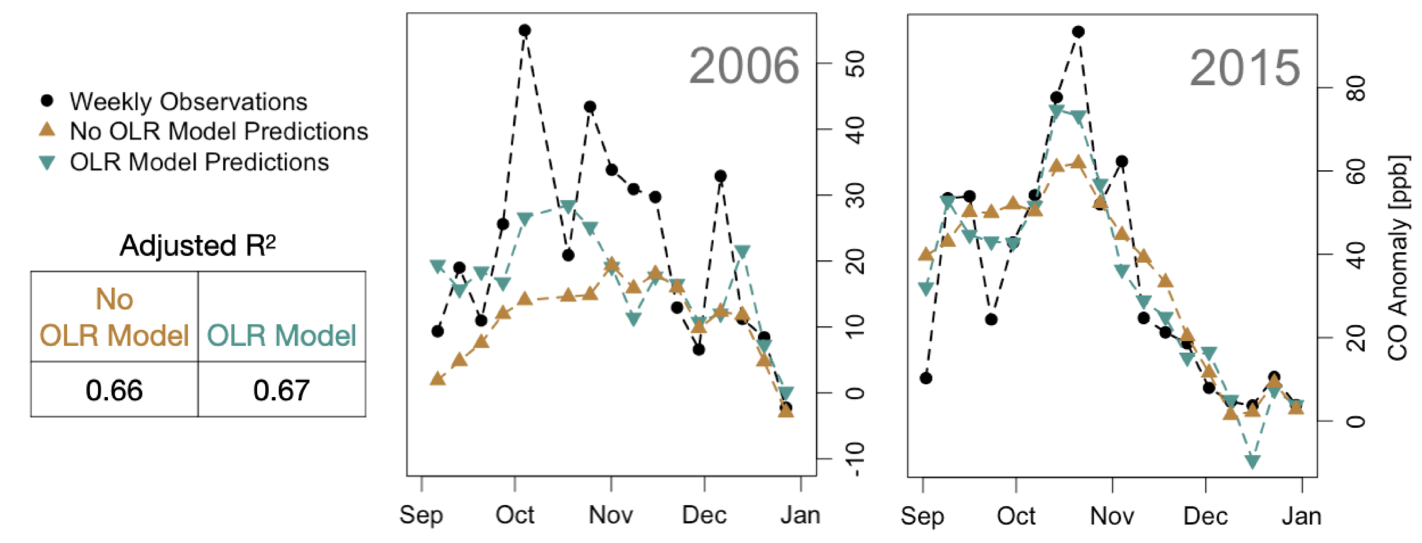

Figure 4: Model predictions in two extreme years highlighting OLR contribution.

- Increasing the minimum lag allowed in the model pushes out the prediction horizon. At a 6 month lead time, the model captures the shape of the 2015 spike and explains 68% of the variability.

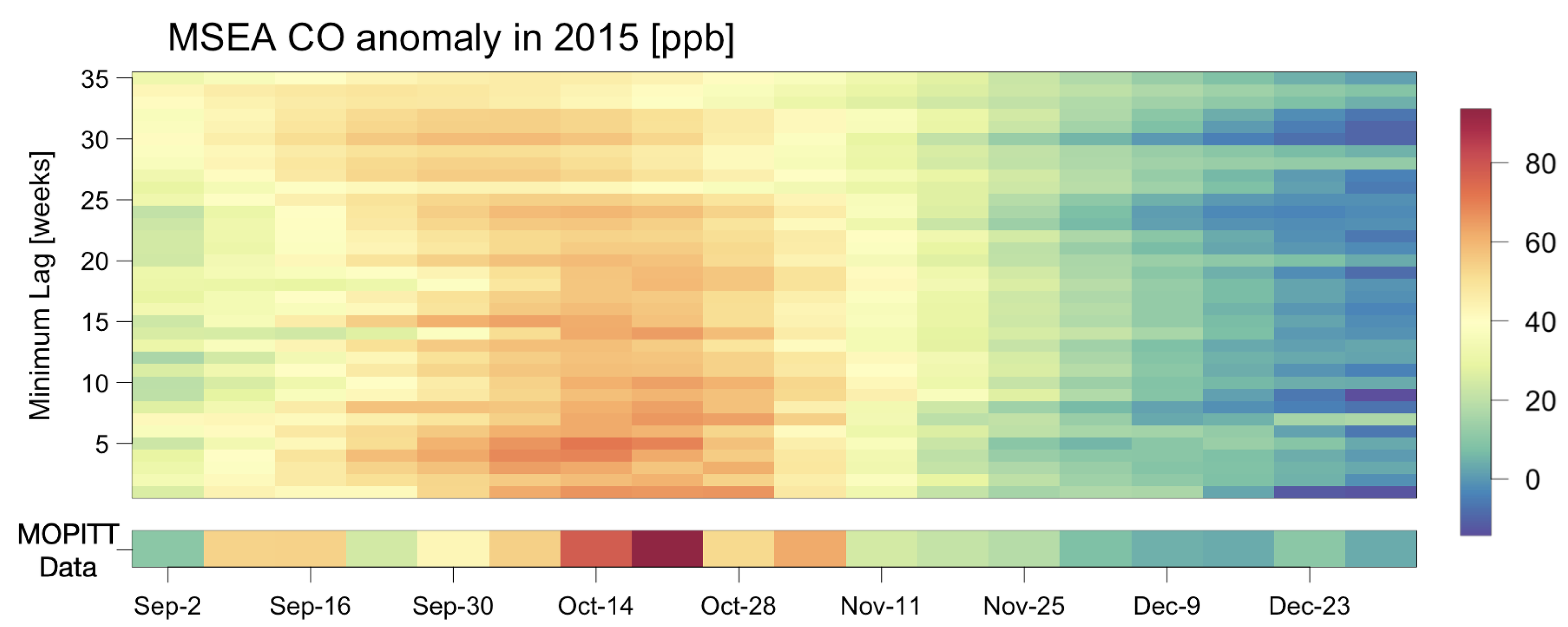

Figure 5: 2015 CO predictions as a function of minimum lag (prediction horizon).

Conclusions

1. Multiple lags of a single index are important for explaining CO.
2. Including OLR helps capture extreme CO anomalies in MSEA.
3. Model explains 68% of CO variability at 6 month lead time, making it a useful tool for fire season preparedness.

For more details, see Daniels et al. preprint!

References

[1] R. R. Buchholz et al. "Links Between Carbon Monoxide and Climate Indices for the Southern Hemisphere and Tropical Fire Regions.". In: *Journal of Geophysical Research: Atmospheres* 123 (2018). DOI: 10.1029/2018JD028438.

[2] W. S. Daniels et al. "Predicting Fire Season Intensity in Maritime Southeast Asia with Interpretable Models.". In: *EarthArXiv* (2021). DOI: 10.31223/X59320.